

Original Articles

Relationship between climate change and low-carbon agricultural production: A case study in Hebei Province, China

Yuping Bai^{a,b,c}, Xiangzheng Deng^{a,b,c,*}, Sijian Jiang^{a,b,c}, Zhe Zhao^d, Yi Miao^e^a Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China^b Center for Chinese Agricultural Policy, Chinese Academy of Sciences, Beijing 100101, China^c University of Chinese Academy of Sciences, Beijing 100149, China^d School of Economics & Management, Beijing Forestry University, Beijing 100083, China^e College of Geography and Environment, Shandong Normal University, Jinan 250358, China

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ABSTRACT

With the increase of greenhouse gas (GHG) emissions in the atmosphere, global greenhouse effects have intensified, thereby contributing to climate change. Agriculture contributes to climate change by increasing GHG emissions, and climate change in turn affects agricultural production. In this paper, we calculated carbon emissions and sequestration of agriculture in the 142 counties of Hebei Province, China, and analyzed their spatiotemporal distributions during 2000–2010. Considering net carbon emissions as an undesirable output, we then measured low-carbon agricultural production efficiency using a stochastic directional distance function. We further explored the impacts of climate change on low-carbon agricultural production. We found that carbon emissions in agriculture increased by 15.85% (650 million tons) during 2000–2010, while carbon sequestration in agroecosystems increased by 33.82% (13.8 million tons). The annual average low-carbon agricultural production efficiency increased by 3.03%. There were distinct disparities of efficiency among cities, with the highest efficiency in Chengde and Shijiazhuang. The efficiency in southeastern areas was lower than that in the northwest, owing to the increased carbon emissions. Temperature and precipitation had a positive effect on efficiency in Hebei, whereas extreme weather events caused lower efficiency. The results provide valuable references for developing sustainable, climate-resilient and adaptive agriculture under changing climatic conditions.

1. Introduction

With the increase of greenhouse gas (GHG) emissions in the atmosphere, the global greenhouse effect has intensified, thereby contributing to climate change and a series of environmental and ecological problems. GHG emissions have a dramatic impact on human wellbeing (Chen et al., 2013). The IPCC Fifth Assessment Report (AR5, 2013) indicates that GHG emissions from human activity are the main reason for global warming. Secondary and tertiary industries are the leading sectors for generating carbon emissions (Wang et al., 2016). However, the rapid development of agriculture accelerates global climate change. Agriculture directly contributes 10%–12% of global anthropogenic GHG emissions (Smith et al., 2008; Nayak et al., 2015). Carbon emissions from agriculture account for 16% to 17% of GHG emissions in China (Tian et al., 2012), and about 6% to 7% in the United States (Johnson et al., 2007). With the acceleration of agricultural modernization, increasing agricultural inputs and greater use

of agricultural machines have increased carbon emissions in China. Agroecosystems have an important role in carbon sequestration (Álvaro-Fuentes and Paustian, 2011; Lal, 2011; Zhan et al., 2012). Crops can absorb carbon dioxide emissions through photosynthesis, which effectively reduces carbon emissions to the atmosphere (Hutchinson et al., 2007).

Carbon emission reduction responses to climate change have become globally recognized. Although carbon emissions from agriculture are lower than those from secondary and tertiary industry, the potential of carbon reduction in agroecosystems and the positive external effects of carbon reduction cannot be ignored (Smith et al., 2000; Vlek et al., 2004; Chen et al., 2013). Carbon reduction in agriculture through the use of organic fertilizers and low-carbon technology improves soil nutrients and agroecosystem productivity, which is important in developing sustainable, low-carbon and climate-resilient agriculture (Meisterling et al., 2009; Beddington et al., 2011; Pathak and Aggarwal, 2012). However, the performance of low-carbon agricultural

* Corresponding author at: Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China.
E-mail address: dengxz@igsnrr.ac.cn (X. Deng).

production in China remains unquantified. In addition, it is not clear how we should measure the performance under the constraints of carbon emissions. These questions require discussion under the pressing need for carbon reduction and climate change mitigation.

Several methods have been examined for the evaluation of production technical efficiency. From an input and output perspective, such measurement methods generally include a parametric Stochastic Frontier Analysis (SFA) and a non-parametric Data Envelope Analysis (DEA) (Wadud and White, 2000). Inappropriate production function form could cause incorrect conclusions (Dyckhoff and Allen, 2001). The DEA model can avoid inappropriate production function form because it does not require the construction of specific function forms (Song et al., 2012; Bai et al., 2017). However, DEA can cause errors in the performance evaluation because it ignores the random noise, especially when it is applied for macroeconomic data (Yang et al., 2016). In contrast, SFA takes into consideration random errors and inefficiency in the form of a production function. Based on the SFA method, Cabrera et al. (2010) estimated technical efficiency of 273 Wisconsin dairy farms and identified the determinants of the technical efficiency. Essilfie et al. (2011) measured technical efficiency in small-scale maize production in the Mfantseman Municipality of Ghana. However, little research has focused on the evaluation of the agricultural production efficiency under the constraints of undesirable outputs (such as GHG emissions). This paper proposed an improved method to measure performance of low-carbon agricultural production by using a stochastic directional distance function, which couples the Directional Distance Function (DDF) and SFA methods.

While agriculture contributes to global climate change by increasing gas emissions to the atmosphere, climate change in turn affects agricultural production by altering the growth, yield and nutritional quality of crops (Caldwell et al., 2005). The IPCC Fifth Assessment Report (AR5, 2013) indicates that climate change is more severe than currently recognized. With the increase of atmospheric carbon dioxide concentration and global warming, the impacts of climate change on grain production and food security has become an important research topic (Di Falco et al., 2011; Wheeler and Von Braun, 2013). Wang et al. (2009) analyzed the effects of temperature and precipitation on net crop revenues using cross-sectional data from 8405 households across 28 provinces of China, finding that global warming assists irrigation agriculture but runs against rain-fed agriculture. Huang et al. (2010) conducted an econometric analysis of the impacts of climate change on grain production at county-level in China. They stated that the increase of temperature had a positive effect on grain production in North and Northwest China but a negative effect along its eastern coast and south of the Yangtze River.

Some recent research has focused on the impacts of climate change on agricultural production, whereas other research has concentrated on carbon emissions and climate change mitigation by agriculture. However, less attention has been paid to the interrelationship between these two aspects (Yan et al., 2015; Liu et al., 2014). In particular, no quantitative indicator system has been built to assess the performance of low-carbon agricultural production under the constraints of climate change mitigation. Additionally, influences on the performance of low-carbon agricultural production, especially from the perspective of climate change, have not been elucidated. Therefore, taking Hebei Province as the study area, our specific aims were to: (1) calculate carbon sequestration and carbon emissions in agroecosystem and analyze their spatiotemporal distributions during 2000–2010; (2) develop and apply a stochastic directional distance function to measure low-carbon agricultural production efficiency, considering net carbon emissions in agroecosystems as an undesirable output; (3) explore the impacts of climate change on low-carbon agricultural production efficiency.

2. Study areas and data

2.1. Study areas

Hebei Province, surrounding the capital city Beijing and Tianjin, is in the middle-north of China ($36^{\circ}05'N$ – $42^{\circ}40'N$, $113^{\circ}27'E$ – $119^{\circ}50'E$), with the lower reaches of the Yellow River to the north and Bohai Sea to the east. The main land-cover types in the province include plateaus, mountains, hills, basins and plains. It has a total area of 18.88 million ha, covering 115 county administrative level units. Owing to the temperate continental monsoon climate, precipitation in the province decreases from the east and southeast to the west and northwest. According to the monitoring data of meteorological stations from China's national weather bureau, annual precipitation was between 384.1 and 889.9 mm in 2010. The elevation was higher in the northwestern part than in the southeast. Affected by the terrain, annual temperature also increased from the northwest to southeast. The highest annual average temperature in Hebei Province during 2000–2010 was $14.3^{\circ}C$, and the lowest $2.9^{\circ}C$. The distribution of precipitation in Hebei Province dramatically changed between 2000 and 2010. There was a strong increasing trend in the north and substantial decreasing trend in the south (Fig. 1). The temperature varied both spatially and temporally, which affected natural ecosystems and human activities, especially of industries dependent on climate, such as agriculture.

As one of the main grain production areas in China, agriculture is important to economic progress and social stability in Hebei Province (Deng et al., 2017b). The area of cultivated land of the province is 6.47 million ha, accounting for 34.27% of the total area. The rural population was 3.99 million in 2010, more than 55% of the total population. In that year, grain yield of the agricultural sector was 29.76 million tons, increasing by 16.66% above 2000 levels, but the growth rate decreased (Fig. 2). With climate change and increasing population, the conflict between food demand and grain production in Hebei Province is increasing. Climate change affects grain production by altering growth and yield and the nutritional quality of crops, whereas agriculture is in turn contributing to global climate change by increasing carbon emissions to the atmosphere. Therefore, it still needs further research to measure low-carbon agricultural production efficiency and explore the relationship between climate change and low-carbon agricultural production.

3. Methods and data

3.1. Evaluation of carbon emissions and carbon sequestration in agriculture

Carbon emissions in an agroecosystem is mainly from human agricultural production activities such as irrigation, fertilization, pesticides, farm machinery and plastic mulch. It is estimated by

$$E_t = G_f A + (A_m B + W_m C) + A_i D + F_a E + P_p F, \quad (1)$$

where E_t is the amount of carbon emissions, G_f , A_m , W_m , A_i , F_a and P_p are fertilizer use, sown area, total power of agricultural machinery, irrigated area, plastic mulch and pesticide use, respectively. A , B , C , D , E and F are transformation parameters, which were estimated by Lal (2004), Zhang et al. (2013) and Tian and Zhang (2013) as shown in Table 1.

Carbon sequestration in an agroecosystem is mainly from the photosynthesis of crops such as wheat, cotton, vegetables, corn and tobacco. It is estimated by

$$C_t = \sum_i C_{di} = \sum_i C_{fi} D_{wi} = \sum_i C_{fi} Y_{wi} / H_i, \quad (2)$$

where C_t is the amount of carbon sequestration, C_{di} is the amount of carbon sequestration by crop i , C_{fi} is the carbon absorption rate, Y_{wi} is the economic yield of i , D_{wi} is the biomass of i , and H_i is the economic

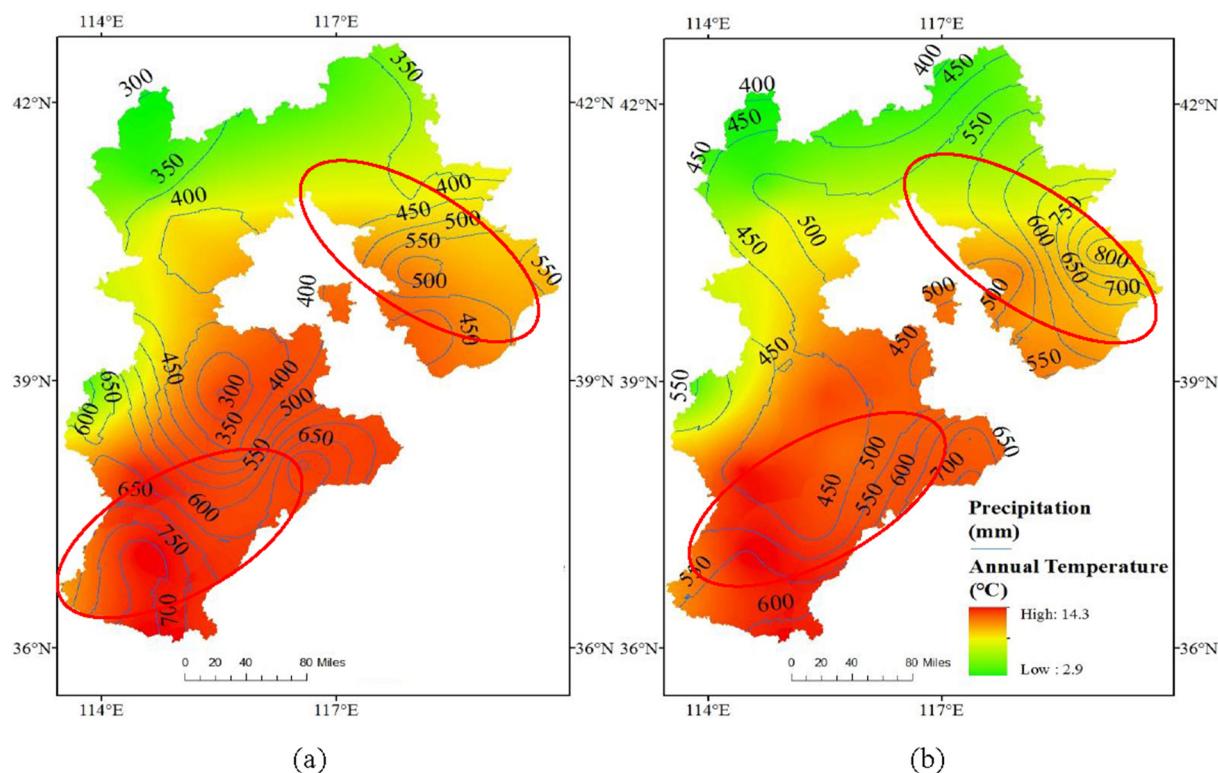


Fig. 1. Hebei Province temperature and precipitation in 2000 (a) and 2010 (b). (Source: The monitoring data of meteorological stations from China's National Weather Bureau.)

coefficient of i . Table 2 shows carbon absorption rates and economic coefficients of i .

Therefore, net carbon emissions (C_{nt}) in an agroecosystem can be defined as

$$C_{nt} = E_t - C_t \quad (3)$$

3.2. Measurement of low-carbon agricultural production efficiency

Considering net carbon emissions as an undesirable output, we used a stochastic directional distance function to measure low-carbon agricultural production efficiency of 142 counties in Hebei Province. Directional distance function (DDF) simultaneously allows for the expansion of desirable outputs and contraction of undesirable outputs (Lee et al., 2002; Watanabe and Tanaka, 2007; Bai et al., 2016), which can objectively depict agricultural production activities.

Table 1
Carbon emission coefficients of carbon sources in agroecosystems.

Variable	Unit	Coefficient
A	kg/Mg	857.54
B	kg/ha	16.47
C	kg/kW	0.18
D	kg/ha	266.48
E	kg/Mg	5180
F	kg/Mg	4702.38

3.2.1. Directional distance function

Suppose a vector of input $x = (x_1, \dots, x_N) \in R_N^+$ can produce a vector of desirable output $y \in R_M^+$ and a vector of undesirable output $c \in R_L^+$ (Färe et al., 2005). We describe the technology by

$$T(x,y,c) = \{(x,y,c): x \text{ can produce } y \text{ and } c\}, \quad (4)$$

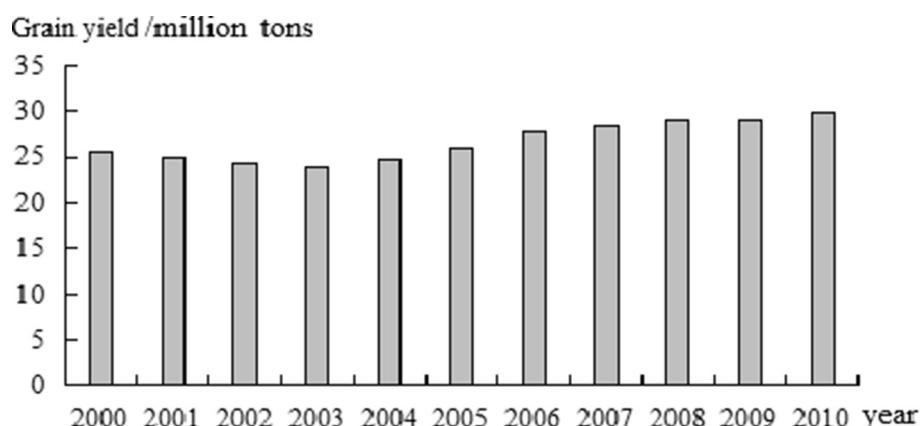


Fig. 2. Grain yield of Hebei Province during 2000–2010. (Source: The Rural Statistic Yearbook of Hebei Province (2001–2011)).

Table 2

Carbon absorption rate and economic coefficient of crops.

Crop	Paddy	Wheat	Cotton	Soybean	Oilplant	Corn	Sugarplant	Tobacco	Vegetable	Fruit
H	0.45	0.4	0.1	0.34	0.32	0.4	0.7	0.55	9.5	1.75
C	0.4144	0.4835	0.45	0.45	0.45	0.4709	0.4072	0.45	0.45	0.45

and the output set can be described as

$$P(x) = \{(y, c): x \text{ can produce } y \text{ and } c\}. \quad (5)$$

The DDF, which can produce desirable output and reduce undesirable output can be defined as

$$D(x, y, c; g_y, g_c) = \sup \{\beta: (y + \beta g_y, c - \beta g_c) \in P(x)\} \quad (6)$$

where $g = (g_y, g_c)$ is a directional vector, which indicates that the desirable output increases in the direction of g_y and the undesirable output decreases in the direction of g_c ; β is the maximum proportion of this expansion and reduction; $D(x, y, c)$ indicates this maximum growth ratio and reduction ratio.

3.2.2. Estimation of the stochastic directional distance function

To empirically estimate the DDF using parametric approaches, the specific form of the function should be set, including Cobb-Douglas, translog and quadratic forms. A quadratic DDF is used in this paper:

$$\begin{aligned} D(x, y, c) = & \beta_0 + \sum_{n=1}^N \beta_n x_n + \beta_y y + \beta_c c + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} x_n x_m \\ & + \sum_{n=1}^N \beta_{ny} x_n y + \sum_{n=1}^N \beta_{nc} x_n c + \frac{1}{2} \beta_{yy} y^2 + \frac{1}{2} \beta_{cc} c^2 + \nu, \end{aligned} \quad (7)$$

where ν is a random variable accounting for statistical noise and errors of approximation.

The DDF has translation property, which means if the desirable output increases by α in the direction of g_y and the undesirable output decreases by α in the direction of g_c , the value of distance function will increase by α . The translation property is described by

$$D(x, y + \alpha g_y, c - \alpha g_c; g_y, g_c) = D(x; g_y, g_c) - \alpha. \quad (8)$$

Setting $\alpha = c$ and defining $[D(x, y, c; g_y, g_c)] = u \geq 0$, we can transform Eq. (7) into

$$\begin{aligned} -c = & \beta_0 + \sum_{n=1}^N \beta_n x_n + \beta_y (y + c) + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} x_n x_m \\ & + \sum_{n=1}^N \beta_{ny} x_n (y + c) + \frac{1}{2} \beta_{yy} (y + c)^2 + \nu - u, \end{aligned} \quad (9)$$

where $u = D(x, y, c; g_y, g_c)$ is a non-negative variable that represents time-varying technical inefficiency and is assumed independent of random variable ν . It is related to a set of exogenous variables as

$$u = \delta Z + w, \quad (10)$$

where $w \sim N^+(Z\delta, \sigma_U^2)$, which is assumed to be a random variable that has a normal distribution truncated at zero with constant variance σ_U^2 . δ is a vector of unknown coefficients to be estimated; and Z is a vector of factors that directly affects inefficiency.

3.3. Data

We used agricultural aggregate panel data of 142 counties in Hebei Province during 2000–2010, and agricultural input data and economic yield of various crops to evaluate carbon emissions and sequestration in the agroecosystem. For further measuring low-carbon agricultural production efficiency, we used agricultural production input data, including fertilizer use, sown area, total power of agricultural machinery, plastic mulch and pesticide use (Neumann et al., 2010; Shi et al., 2013;

Cao et al., 2014), and output data including agricultural GDP (desirable output) and net carbon emissions in the agroecosystem (undesirable output). All these data were taken from the *Rural Statistic Yearbook of Hebei Province (2001–2011)* and the *Hebei Economic Yearbook (2001–2011)*.

We also identified the limiting factors of production inefficiency based on additional geographical and meteorological data to explore the relationship between climate change and agricultural production. Meteorological data including annual temperature, annual precipitation, sunshine hours and relative humidity were from monitoring data of meteorological stations from China's National Weather Bureau, and land productivity was estimated by Deng et al. (2017a). These data were originally at 1 km × 1 km resolution but were integrated to county level. Descriptive statistics for the variables used in the stochastic directional distance function are shown in Table 3.

Table 4 illustrated the correlation matrix for independent variables used in the estimation. As shown, correlation coefficients between different independent variables were below 0.6 except coefficients between sown area and farm machinery power. Moreover, their variance inflation factor was much smaller than 4, indicating that there was no evidence of the existence of multicollinearity.

4. Results

4.1. Carbon emissions and carbon sequestration in agroecosystems

Carbon emissions in agroecosystems were estimated from six types of carbon sources, including irrigation, fertilizer use, sowing, farm machinery, mulching film and pesticide use in Hebei Province. Fig. 3 showed that the total carbon emissions gradually increased over 2000–2010, from 4100 million tons to 4750 million tons C. Fertilizer use became the largest source of carbon emissions. The amount of carbon emissions of fertilizer use increased, reaching 2710 million tons C in 2010. Carbon emissions caused by mulch film and pesticide use increased since 2000 and their amounts in 2010 were 323 million tons and 379 million tons C, respectively. Conversely, carbon emissions of irrigation and sowing remained nearly constant over the period. Farm

Table 3
Summary statistics of variables used in production efficiency estimation.

Variable	Unit	Obs	Mean	Std. Dev.
<i>Input variables</i>				
Agricultural labor (x_1)	person	1562	106659.60	51568.06
Sown area (x_2)	ha	1562	59824.37	28314.88
Fertilizer Use (x_3)	ton	1562	20471.16	14292.37
Plastic Mulch Use (x_4)	ton	1562	373.11	415.69
Pesticide Use (x_5)	ton	1562	537.72	498.70
Farm Machinery Power (x_6)	10^4 kW.h	1562	58.66	45.29
<i>Output variables</i>				
Gross domestic product (y)	10^4 RMB	1562	49971.62	39107.9
Net carbon emission (c)	ton	1562	3.11e+07	1.89e+07
<i>Inefficiency variable</i>				
Temperature (tem)	0.1 °C	1562	126.56	38.95
Annual precipitation ($rain$)	0.1 mm	1562	5115.62	1812.62
Nature disaster ($nadir$)	%	1562	23.83	27.94
Land productivity (lpp)	kg/ha	1562	102004.70	243569.70
Sunshine (sun)	0.1 h	1562	65.16	6.39
Relative humidity (ur)	%	1562	59.81	6.38

Table 4

Correlation matrix for independent variables used in production efficiency estimation.

x_1	x_2	x_3	x_4	x_5	x_6	
x_1	1					
x_2	0.569	1				
x_3	0.458	0.672	1			
x_4	0.166	0.430	0.340	1		
x_5	0.288	0.524	0.631	0.335	1	
x_6	0.237	0.592	0.744	0.222	0.572	1

machinery only accounted for a small part of total emissions, no more than 1%. These results indicated that, in contrast with common perceptions, fertilizer emitted more carbon emissions, rather than power consumption by farm machinery.

Through crop photosynthesis, carbon dioxide emissions can be turned into organic matter for crop growth. In the present study, we used 10 types of major crops in Hebei Province to estimate carbon sequestration in agroecosystems. The crops were divided into three categories: grain crops (paddy, wheat, soybeans, and corn), cash crops (cotton, tobacco, oil plants, and sugar plants), and fruits and vegetables. Fig. 4 showed that total agriculture carbon sequestration declined slightly before 2003 and then gradually increased during 2000–2010, from 40.8 million tons to 54.6 million tons C. Grain crops occupied the largest part of total carbon sequestration, reaching 42 million tons C in 2010. The amount of carbon sequestration for fruits and vegetables was 7 million tons C. The cash crop took up the smallest part, only absorbing 4 million tons C. These results reflected the crop structure of Hebei Province. Grain crops are not only important to satisfy human food demands but contribute substantially to carbon sequestration.

We then calculated net carbon emissions. Their total amount in the province had a strong increasing trend over 2000–2010, especially in southern and eastern areas. Net carbon emissions of the 142 counties was from 17 million tons to 57 million tons C, with a slight effect of carbon sequestration compared with a large amount of carbon emissions. The spatial distribution (Fig. 5) showed that net carbon emissions in southern and northeastern portions were clearly greater than those in northern and northwestern areas. The major net carbon emission counties contained economically and agriculturally developed cities, such as Shijiazhuang, Tangshan and Cangzhou. The results also revealed that carbon emissions from agricultural production increased faster than carbon sequestration.

4.2. Relationship between low-carbon agricultural production efficiency and climate change using the stochastic directional distance function

Based on the estimating results of net carbon emissions in agroecosystem, we developed a stochastic directional distance function to measure low-carbon agricultural production efficiency. The main advantages of this improved method include both sides. Stochastic Frontier Analysis had taken random errors and inefficiency into consideration in the form of a production function, as avoiding the problems in the other efficiency evaluation models which ignores the random noise, especially when it is applied for macroeconomic data. By coupling the Directional Distance Function with Stochastic Frontier Analysis, we could measure low-carbon agricultural production efficiency by considering net carbon emissions in agroecosystems as an undesirable output. It improved traditional methods for evaluation of agricultural production efficiency, which cannot take environmental negative effects in the process of agricultural production into account. The efficiency term distribution was skewed to the left, indicating that the results were consistent with the hypothesis of the estimation model (Fig. 6). Maximum likelihood estimates of the stochastic directional distance function are shown in Table 5.

4.2.1. Parameter estimation

Table 5 revealed that more than half the parameters estimated were statistically significant within 10% level. The coefficients of fertilizer use, sown area, total power of agricultural machinery, plastic mulch and pesticide use (β_2 – β_6) were negative, implying that these agricultural inputs caused greater carbon emissions in agroecosystems. The coefficient of agricultural labor (β_1) was positive, indicating that the larger the agricultural labor force was, the lower the carbon emissions were.

Fig. 6 also illustrated that the efficiency of most counties (more than half of the 142) were within the range 0.80–0.95. The proportion with efficiency 0.95–1.00 was 12.42%. However, the efficiency of 14.35% counties was still lower than 0.80, and some even within the range 0.60–0.70. These results revealed that although most counties in the province had moved into a stage of high agricultural production efficiency under the constraints of carbon emissions, we cannot ignore the differences between counties. The low-level counties deserve more attention and support toward promoting low-carbon agricultural production efficiency.

4.2.2. Spatiotemporal patterns of low-carbon agricultural production efficiency

The annual average low-carbon agricultural production efficiency in Hebei Province increased by 3.03% (0.026) over the period 2000–2010. This was because agricultural productivity and grain yield improved

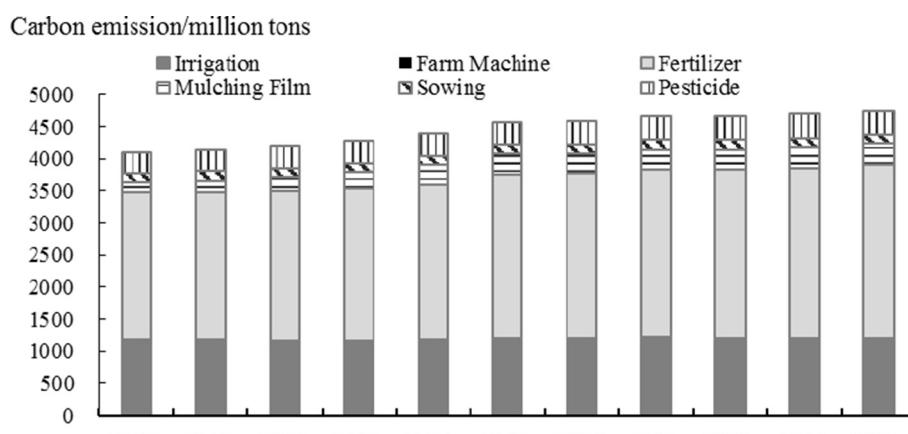


Fig. 3. Carbon emissions from agroecosystems Hebei Province during 2000–2010.

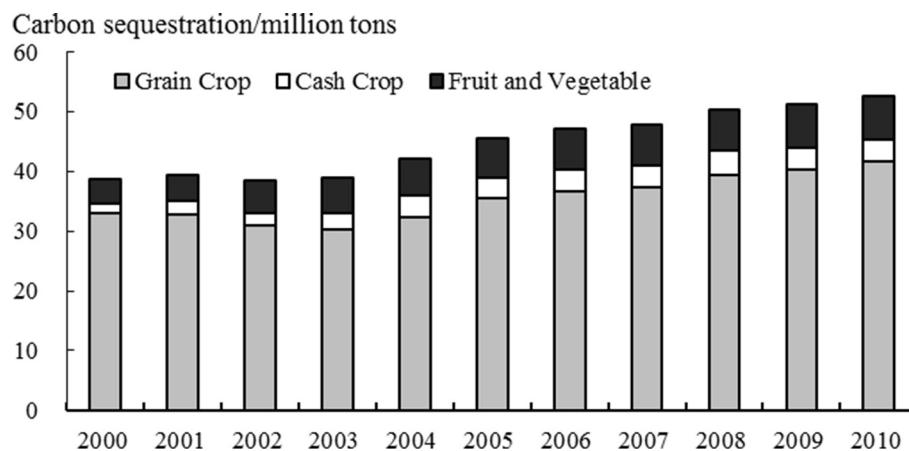


Fig. 4. Carbon sequestration in agroecosystems Hebei Province during 2000–2010.

after the policy of supporting agriculture and benefiting farmers was implemented, and the amount of carbon sequestration in agroecosystems also increased during this period. Fig. 7 presented the differences of efficiency among cities in the province during 2000–2010, showing that the efficiency in Chengde and Shijiazhuang was high with an annual average efficiency over 0.90. Hengshui, Cangzhou and Tangshan had relatively low efficiencies among all cities in the province at 0.80, 0.83 and 0.84 respectively. All provincial cities showed an increasing trend over the time period 2000–2010. However, cities with lower agricultural production efficiencies had a higher annual rate of increase than those achieving high efficiency during the decade. These results revealed a breakthrough in Hebei Province toward promoting low-carbon agricultural production efficiency.

With economic progress, the low-carbon agricultural production efficiency in the province showed an increasing trend over the entire area (Fig. 8). Regarding regional differences, high agricultural production efficiency regions were mainly in economically developed areas, especially the southwest, which contained the provincial capital city Shijiazhuang. Because of the high carbon emissions in agroecosystems, the low-carbon agricultural production efficiency in

southeastern areas was less than those in northern and western areas. Although the northern cities remained at a relatively low economic development level, they had higher production efficiency and were more environmentally friendly. Temporally, most areas maintained a stable production efficiency, and some counties in the mid-south achieved some progress in efficiency. However, in 2010, most counties in eastern parts of Hebei Province remained at a low efficiency level (< 0.80). These counties have much room for improvement in terms of lifting agricultural output and reducing carbon emissions.

4.3. Impacts of climate change on low-carbon agricultural production efficiency

Table 4 also showed that all the limiting variables of inefficiency were statistically significant at least at the 10% level. Specifically, the coefficient of variable temperature has a negative sign, implying that the higher temperature, the lower the technical inefficiency and the higher the low-carbon agricultural production efficiency. The variable annual precipitation was significantly negatively correlated with the inefficiency term, implying that annual precipitation also had a positive

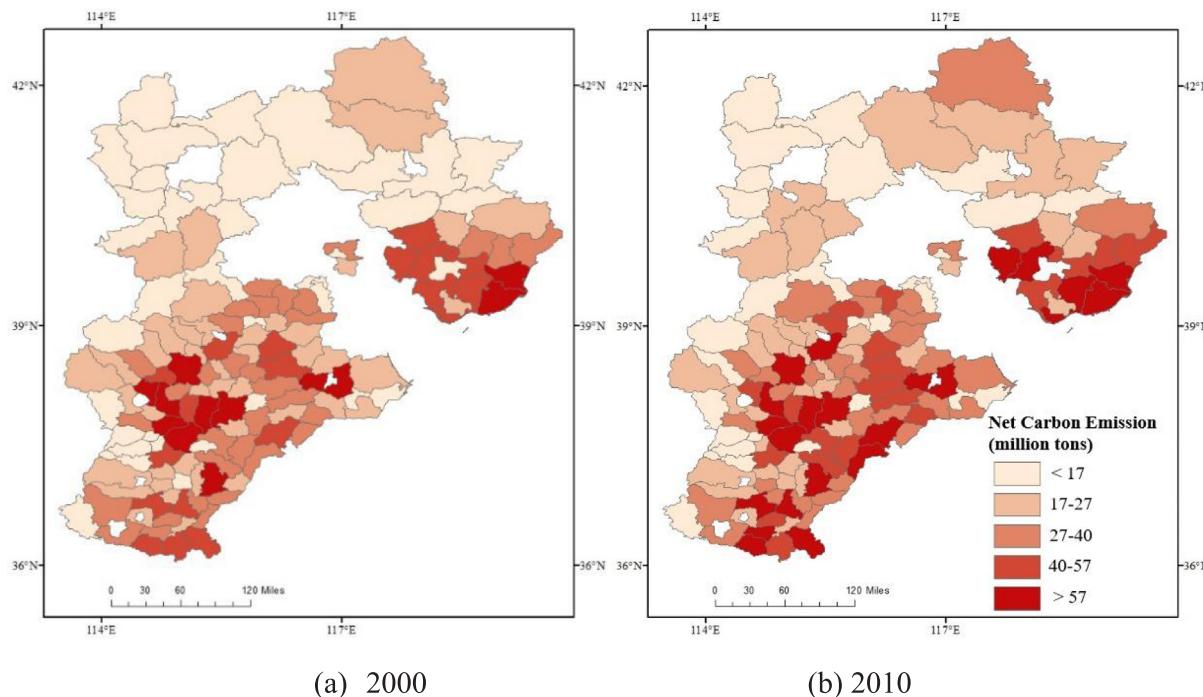


Fig. 5. Net carbon emission in 2000 (a) and 2010 (b) for Hebei Province.

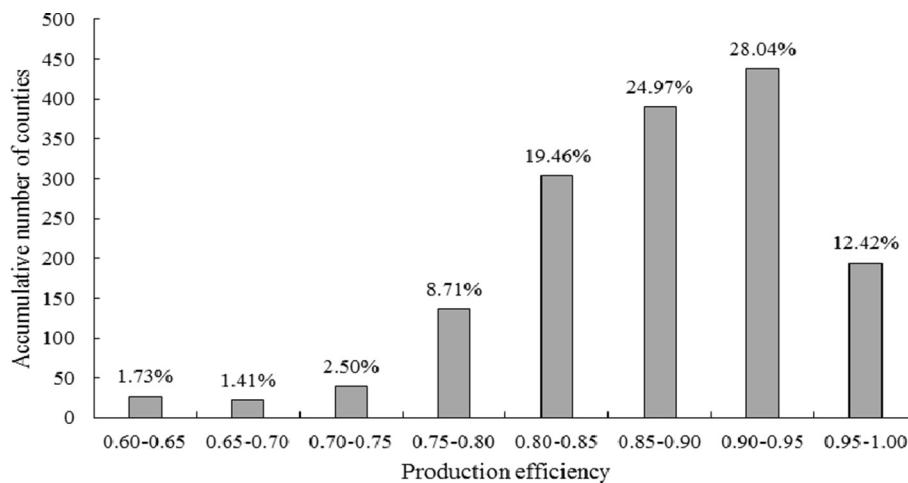


Fig. 6. Distribution of production efficiency of the 142 counties of Hebei Province during 2000–2010.

Table 5

Parameter estimates with undesirable output.

	Variable	Parameter	Coefficient	Std dev.	Z		Variable	Parameter	Coefficient	Std dev.	Z
Inputs	Intercept	β_0	-0.029 ^{**}	0.010	-2.850	Desirable outputs	y	β_y	0.018	0.017	1.050
	x_1	β_1	0.089 ^{***}	0.013	6.710	Undesirable outputs	y^2	β_{yy}	0.150 ^{***}	0.019	7.760
	x_2	β_2	-0.063 ^{***}	0.022	-2.820	Inputs-outputs	c	β_c	-	-	-
	x_3	β_3	-0.695 ^{***}	0.017	-41.690		c^2	β_{cc}	-	-	-
	x_4	β_4	-0.061 ^{***}	0.004	-14.540		yx_1	β_{1y}	0.002	0.011	0.190
	x_5	β_5	-0.085 ^{***}	0.008	-10.530		yx_2	β_{2y}	-0.087 ^{***}	0.017	-5.000
	x_6	β_6	-0.020 [*]	0.011	-1.820		yx_3	β_{3y}	-0.111 ^{***}	0.017	-6.640
	x_1^2	β_{11}	-0.020	0.014	-1.490		yx_4	β_{4y}	-0.017 ^{***}	0.005	-3.140
	x_2^2	β_{22}	0.036 [*]	0.019	1.950		yx_5	β_{5y}	0.002	0.007	0.220
	x_3^2	β_{33}	0.086 ^{***}	0.017	5.000		yx_6	β_{6y}	0.011	0.007	1.590
	x_4^2	β_{44}	-0.004 ^{***}	0.001	-3.580		yc	β_{cy}	-	-	-
	x_5^2	β_{55}	-0.005 ^{**}	0.002	-2.290		cx_1	β_{1c}	-	-	-
	x_6^2	β_{66}	-0.005	0.005	-1.050		cx_2	β_{2c}	-	-	-
	$x_1 x_2$	β_{12}	-0.013	0.013	-1.010		cx_3	β_{3c}	-	-	-
	$x_1 x_3$	β_{13}	-0.016	0.013	-1.250		cx_4	β_{4c}	-	-	-
	$x_1 x_4$	β_{14}	0.004	0.003	1.390		cx_5	β_{5c}	-	-	-
	$x_1 x_5$	β_{15}	-0.006	0.005	-1.010		cx_6	β_{6c}	-	-	-
	$x_1 x_6$	β_{16}	-0.022 ^{***}	0.007	-3.100	Zs	Constant	z_0	1.140 ^{***}	0.071	16.160
	$x_2 x_3$	β_{23}	0.055 ^{***}	0.018	2.990		tem	z_1	-0.100 [*]	0.060	-1.670
	$x_2 x_4$	β_{24}	-0.009 [*]	0.004	-1.930		rain	z_2	-0.04 ^{***}	0.008	-4.900
	$x_2 x_5$	β_{25}	0.002	0.007	0.310		nadir	z_3	0.037 ^{***}	0.002	18.820
	$x_2 x_6$	β_{26}	0.005	0.009	0.520		lpp	z_4	-0.014 ^{**}	0.007	-2.100
	$x_3 x_4$	β_{34}	0.033 ^{***}	0.004	7.660		sun	z_5	-0.066 ^{**}	0.029	-2.290
	$x_3 x_5$	β_{35}	0.013 ^{**}	0.006	2.180		ur	z_6	0.043 ^{***}	0.020	2.100
	$x_3 x_6$	β_{36}	0.006	0.007	0.850		η		0.020 ^{***}	0.002	9.33
	$x_4 x_5$	β_{45}	-0.007 ^{***}	0.002	-4.060	Number of observations = 1562					
	$x_5 x_6$	β_{56}	0.007 ^{**}	0.004	1.960	Prob > Chi2 = 0.0000 Log-likelihood function = 3383.3371					

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

effect on low-carbon agricultural production efficiency in Hebei Province. Land productivity and sunshine were also negatively associated with the inefficiency term, suggesting that higher land productivity and more sunshine enhanced low-carbon agricultural production efficiency. However, natural disasters were significantly positively correlated with the inefficiency term, implying that a higher frequency of extreme weather events reduced agricultural production efficiency. All these results revealed that climate change had complex effects on low-carbon agricultural production efficiency.

5. Discussion

There are many relevant studies focused on evaluating the effects of climate change on agricultural production, and some have concentrated on carbon emissions and climate change induced by agriculture (Lobell

and Gourdji, 2012; Wang et al., 2009). However, less attention has been paid to their interrelationships. In the present study, we quantitatively explored the relationship between climate change and low-carbon agriculture. In particular, we constructed a quantitative indicator system to assess the efficiency of low-carbon agricultural production under the constraints of climate change mitigation. Furthermore, we discerned influences on efficiency from the perspective of climate change. This integrated research gives references for developing sustainable, climate-resilient and low-carbon agriculture under changing climatic conditions. The methods we applied can also be applied as reference to similar research in other study areas.

Low-carbon agriculture is used to mitigate global climate change and advance food security (de Moraes Sá et al., 2017). The present research results showed much room for China to improve its low-carbon agricultural production efficiency, in terms of increasing agricultural

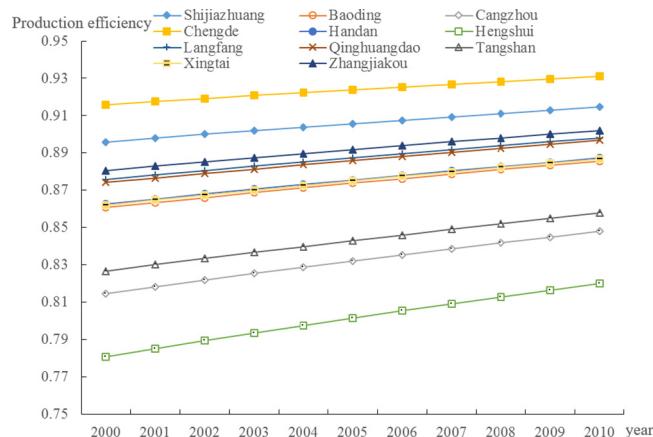


Fig. 7. Low-carbon agricultural production efficiency of cities in Hebei Province during 2000–2010.

output and reducing carbon emissions. This can be done through promoting agricultural conservation tillage, developing carbon trading and developing technologies such as carbon sequestration and use of agricultural biomass (Smith et al., 2007; Kuhn et al., 2016; Friedrich et al., 2017). Temperature and precipitation had positive effects on production efficiency of low-carbon agriculture in Hebei Province, whereas extreme weather events reduced efficiency. This finding is consistent with Piao et al. (2010), who suggested that crop yield in the temperate climate zones of northern China had benefited from increased temperature and precipitation.

We also considered the influences of climate change on low-carbon agricultural production efficiency, but did not identify restrict factors from a socio-economic perspective, such as industrial structure, rural industrialization and rural public investment (Yang et al., 2016). These socio-economic indicators will be included in future research. Finally, the reversibility of carbon sequestration in agroecosystems was not considered in building an indicator system for evaluating carbon emissions from agriculture, which might overestimate low-carbon agricultural production efficiency.

6. Conclusions

The relationship between climate change and agricultural production is much more complex. Although agriculture contributes to global climate change by increasing carbon emissions to the atmosphere, that change in turn affects agricultural production by influencing growth, yield and nutritional quality of crops. In this work, we calculated carbon sequestration and carbon emissions from agroecosystems and analyzed their spatiotemporal distribution in Hebei Province during 2000–2010. Using a stochastic directional distance function, we then measured low-carbon agricultural production efficiency, considering net carbon emissions from agroecosystems as an undesirable output. We further explored the impacts of climate change on the aforementioned efficiency. These findings provide important references for developing sustainable, climate-resilient and adaptive agriculture in China toward maintaining the productivity of agroecosystems under changing climatic conditions.

First, we examined carbon emissions and sequestration in agroecosystems of Hebei Province for 2000–2010. The results showed that carbon emissions in agroecosystems increased by 15.85% (650 million tons) between 2000 and 2010. In this period, fertilizer use became the largest source of carbon emissions other than power consumption by farm machinery. Carbon sequestration in agroecosystems increased by 33.82% (13.8 million tons) over the same period. Although the growth rate of carbon sequestration was more than twice that of carbon emissions, the amount of emissions was much larger than that of carbon sequestration.

Agricultural production efficiency was further measured under the constraints of net carbon emissions. The annual average low-carbon agricultural production efficiency in Hebei Province increased by 3.03% during 2000–2010, from 0.858 to 0.884. This was because of increased grain yield and carbon sequestration in agroecosystems. There were distinct disparities in efficiency among cities in the province; Chengde and Shijiazhuang achieved high efficiencies, whereas Hengshui, Cangzhou and Tangshan had relatively low efficiencies. Spatial distribution analysis indicated that high-efficiency regions were mainly located in economically developed areas such as the southwest, which contained the provincial capital city Shijiazhuang. Moreover,

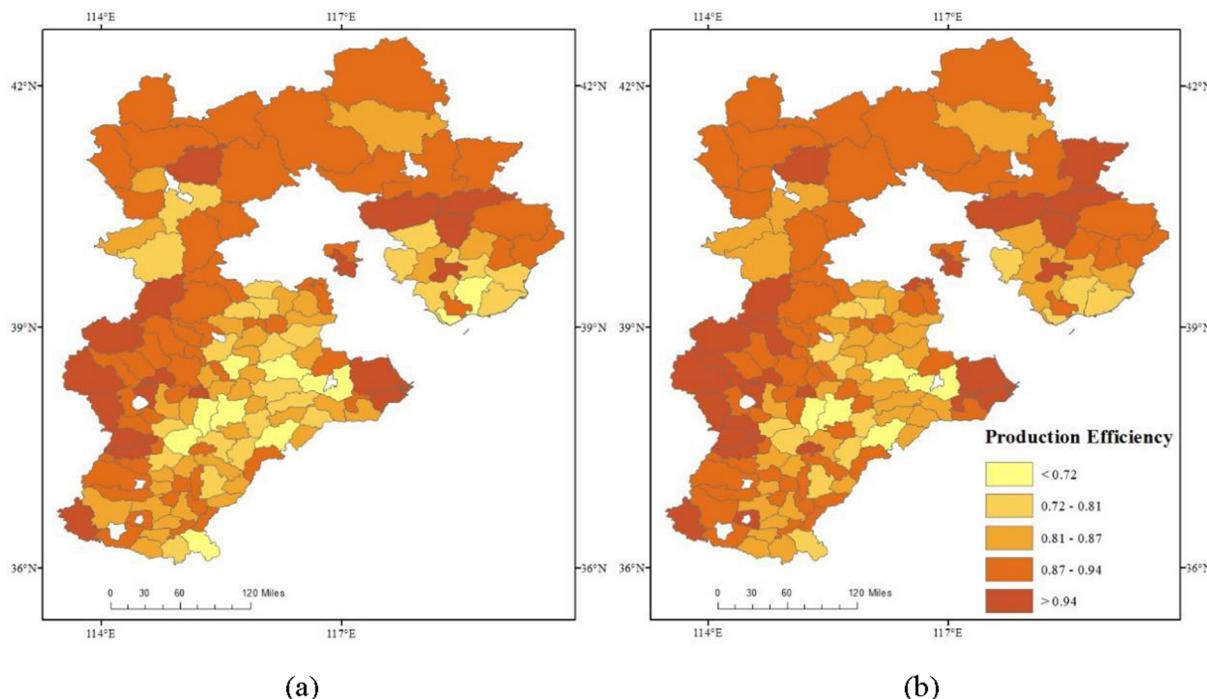


Fig. 8. Spatial patterns of low-carbon agricultural production efficiency in Hebei Province in 2000 (a) and 2010 (b).

because of the more carbon emissions in agroecosystems of southeastern areas, the low-carbon agricultural production efficiency was lower in southeastern areas than in the northwest. These findings revealed much room for their improvement of low-carbon agricultural production efficiency, in terms of raising agricultural output and reducing carbon emissions.

In addition, considering the feedback effects of climate change on agricultural production, we further analyzed the impacts of climate change on low-carbon agricultural production efficiency. The results implied that temperature, precipitation and sunshine had positive effects on improving agricultural production efficiency. However, natural disasters were significantly negatively correlated with agricultural production efficiency, suggesting that a high frequency of extreme weather events reduced agricultural production efficiency. These findings can provide an important reference for developing sustainable, climate-resilient and adaptive agriculture toward maintaining the productivity of agroecosystems under changing climatic conditions.

Finally, based on the research results and relative analysis, we proposed the following policy recommendations. In terms of the carbon emission structure of agricultural production processes, carbon emissions from irrigation, sowing and the use of agricultural machinery remained stable and relatively small. To meet the needs of developing green low-carbon agriculture, more attention should be paid to technological innovations on the process of production and use of fertilizers, pesticides and plastic film. Furthermore, different counties have different agricultural structure and production inputs, leading to the objective gaps of low carbon agricultural efficiency in different counties. Therefore, the connection between regional agricultural structure and agricultural carbon emission distribution should be considered. Based on this analysis, regional agricultural structure and the process of agricultural production should be flexibly adjusted. In addition, the development of low-carbon agriculture should be adapted to regional climate change. The extreme weather, plant diseases and insect pests and other abnormal responses caused by climate change also require research attention. Further work should focus on improving climate change detection and weather prediction. The development of low carbon agriculture should be closely linked with county economy and agricultural science and technology, which should be regarded as the new impetus for regional development.

Conflicts of interest

The authors declare no conflict of interests.

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